Creativity, Learning and AI

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Introduction

Creativity is defined as “tendency to generate or recognize ideas, alternatives, or possibilities that may be useful in solving problems, communicating with others, and entertaining ourselves and others” (Robert E. Franken, 1996). Franken further asserts that being creative means viewing things in a new or different perspective and that it is linked to fundamental ways of how we think for example, Being flexible, tolerance for ambiguity and enjoyment of things which are yet unknown.

As AI is progressing at a rapid pace, it is slowly moving towards more novelness and usefulness. In 1997, IBM Deep Blue defeated chess Grandmaster Garry Kasparov. He believed that Deep Blue’s playing was too human to be that of a machine. In 2017, AlphaGo Zero by google was introduced which was completely self taught. It was only given the details about basic rules of the game Go. In essence, It had the freedom to think in its own way and determine what works best. It too was able to defeat professional human Go Player. In Generative Adversarial Network ie. GAN (Ian J. Goodfellow et. al., 2014), Model acts as the judge for its own creation which gives rise to outputs never seen before. In Creative Adversarial Networks ie. CAN (Elgammal, A. M., Liu, et. al. , 2017), Art is generated by learning about the styles and deviation from the style norms. Researchers at Google are using Artificial Neural Networks (R. E. Uhrig , 1995) to produce music unaided.

However, The current direction of AI is still not able to include the creative learning process in the models. Emily M. and others argue that the language models generated right now are just stochastic parrots which are learning from huge amounts of ingested data but not generating outputs which are too relevant to humans (Emily M. et. al., 2021). Further, The Current AI models such as Artificial Neural Networks (R. E. Uhrig , 1995) lag the interpretability and acts as black box which makes it hard to follow a creative process during the learning to generate something novel and useful.

Creativity makes us humane and modeling it in AI will act as a positive direction towards Strong AI ie. a condition when a machine would be able to apply intelligence to any problem. Moreover, It will aid humans in the creative processes such as music creation, art generation, poem and story writing etc. Incorporating creativity in AI will further help humans understand the process of creativity as models would even be able to generate new ideas and things which we have never seen.

Creativity: Definitions and Characteristics

The Standard definition for creativity is bipartite ie. Creativity requires both originality and effectiveness (Mark A. et. al, 2012). It further adds that originality is important for creativity but it is not sufficient since ideas and products which are original might have no value. It might just be unique or uncommon. Bethune says "Yet familiar as the effects of Genius are, it is not easy to define what Genius is. The etymology of the term will, however, assist us. It is derived from the verb, signifying to engender or create, because it has the quality of originating new combinations of thought, and of presenting them with great clearness and force. Originality of conception, and energy of expression, are essential to Genius." (Bethune, G. W., 1839). Here, Bethune refers to art and genius but he had the assumption that creativity played a role in them. Wikipedia describes creativity as "a phenomenon whereby something new and valuable is formed". The item that is created may be intangible for ex. A theory in science, a story for a movie, joke or just an idea. It may also be a tangible physical object for ex. A Printed Art, An inventive product.

Creativity is fundamental to humans and it is an inescapable challenge for AI (Boden, M. A., 1998). Boden further adds that Creativity is grounded in different everyday tasks for ex. Our ability to associate ideas, perception of the ideas, problem solving using analogical thinking, searching for the solution of a problem using abstract structural spaces. Thus, Creativity involves not just cognition but also emotion and motivation.

There are three types of creativity as described by Boden. It involves generation of novel ideas in different ways. The first type is called "Combinational Creativity" which involves newer combinations of familiar ideas. For example, generation of jokes, wherein using the conceptual structure new jokes can be generated. The second type is "Exploratory Creativity". It involves exploration of the structured conceptual spaces to generate new ideas. The third type which is related to the former is "Transformational Creativity". It involves transformation of the structured conceptual space (one or more dimensions) to generate new ideas. It can generate new ideas which have never been seen before depending on how the transformation has taken place.

The characteristics of creativity which are essential in AI systems (Rowe, J. et. al., 1993) are as follows: 1. Organization of knowledge: It should be organized such that the possible number of associations in the representation can be maximized. This implicates the need of a knowledge representation scheme which is flexible. 2. Tolerance to ambiguity: Systems should be allowed to generate associations which might seem incorrect so as to create connections between the different concepts. 3. Multiple representation : A concept should be applicable to multiple situations and it must be represented in the knowledge. 4. Usefulness of new combinations: The generated new combination should be useful so that not most of the generated combinations are discarded after the extensive computations required for them. 5. Elaborateness of new combinations: The new combinations generated should be verifiable to assess its usefulness.

Creativity in AI: History

Earlier, A large number of programs were created which were based on generative grammars. An idea was represented by a set of rules using symbols. For example: Rumelhart created a story grammar with rules as (Rumelhart, 1975) : Rule 1: Story -> Setting + Episode , Rule 2: Setting -> Time + Place + Characters, Rule 3: Episode -> Event + Reaction . Here terminals are the words and phrases which create the story. It was not a surprise that it was not able to generate good stories due to rigid structure of story generation grammar which is the limitation of grammar based systems.

AM was a transformational system that could discover mathematical concepts (Davis, Lenat, 1982). A set of concepts was used to initialize it where the concept was represented by a set of slots which had details about definitions, some of the examples for the same, domain for operations etc. Initial concepts included functions like union, intersection and general concepts of sets, lists, ordered pairs etc. AM halted after it was not able to produce new and interesting concepts. Lenat argued that a new representation language was needed which could operate at the complexity of heuristics used to generate the concepts. Eurisko (Lenat 1982) was a new program in which heuristics were represented as framed with multiple slots where each slot was a piece of lisp code. Value mutations in slots produced meaningful change in the heuristic. It was used in multiple domains for example, VLSI design, space-ship fleet design etc. However, Eurisko did not go further than AM in the math domain which Lenat attributed to the well explored nature of elementary number theory.

A different approach in the same direction was taken by the BACON family of programs (Langley et. al. 1987). It was designed to model scientific discovery and operated on the basis of data. BACON programs worked by searching using heuristics until suitable laws could be found to describe the given data. It had the creative characteristics of deriving intelligent discoveries from data, but it lacked flexibility, multiple representations as well as explanation of the ideas.

As rule based systems were facing the issue of rigidity, use of meta rules was identified as the solution. It involved creation of rules which could reason and also could create newer rules. MUSCADET was an example of a system based on meta rules (Pastre , 1989). It was a theorem prover for topological linear spaces. The proofs were generated by meta rules guided by heuristics. It was not able to distinguish issues from a mathematical view point. Meta rules brought flexibility but were limited by the pre-determination created by meta rules.

Meanwhile, A flexible representation was implemented using classifier systems (Holland, 1986) which consisted of a collection of rules and a list of messages. On matching the “if” part of the rule matched with a message on the list, it posted “then” part of the matched rule as a new message. Each classifier in the rules list had weights assigned and updated based on matching. Genetic algorithms could further be employed for learning about relevant classifier sets. Thus, Classifier systems were creative due to their flexible representation, tolerance to ambiguity, multiple representation and learning from the environment.

In later systems such as Jape, the grammatical properties were further improved by the use of knowledge networks and use of semantics for its enrichment (Binsted et. al., 1994). It worked on the idea of combinational creativity. Jape produced jokes based on seven general forms of sentences. The semantic network incorporated constituents such as phonology, semantics, syntax etc which were crucial for generation of relevant outputs following proper grammar.

Binsted researched on the outcome of Jape and showed that none of its jokes were exceptionally funny but some were indeed average jokes.

Boden claimed that most current AI-models followed exploration rather than transformation in their creativity grounding (Boden, M. A., 1998). He reasoned that the space transformation may result in structures which do not have any value. The generated ideas could be new but it would not be creative. In order to accommodate transformations, AI models should be able to evaluate the poor quality of newly generated ideas and should prune or update them. However, Evaluation posed issues considering some transformational programs had no evaluative criteria and was being done by humans. Further, A conceptual space which was culturally accepted was needed so that it could increase the relevance with humans and could become useful. Furthermore, Culture and time both impacts the type and acceptance of creativeness ie. a system useful in the current time might not be the same in future and thus the evaluation of creativity becomes subjective and more research is needed to model systems which could include them.

Creativity in AI: Current Progress

Currently, Deep learning powers state of the art creative processes. It is able to include combinational and transformational creativity in the models by the use ANN (R. E. Uhrig , 1995) resulting in novel and useful creations.

One such example is BACON which generates poetry with linguistic style transfer (Pascual, A. R., 2021). It uses the combination of techniques (figure 1) to write poetry which has aesthetic qualities of a given author. It represents the content using Vector Space Model ie. VSM (Melucci M., 2009). It models style using probabilistic models for feature extraction of linguistic elements. Content generator uses LSTM ie. Long Term Short Term Recurrent neural network (Hochreiter et. al., 1997) to generate character outputs. It shows promising results, though the output still needs post-processing from humans. The approach of style transfer from the artist helps in the creation of novel yet useful poems. It also caters to our previous belief that subjective creativity is more useful and thus by allowing it to learn the style from an artist helps the model become valuable to humans. However, It still lacks the general novelness to reach a style which is too far from the data it is trained on.

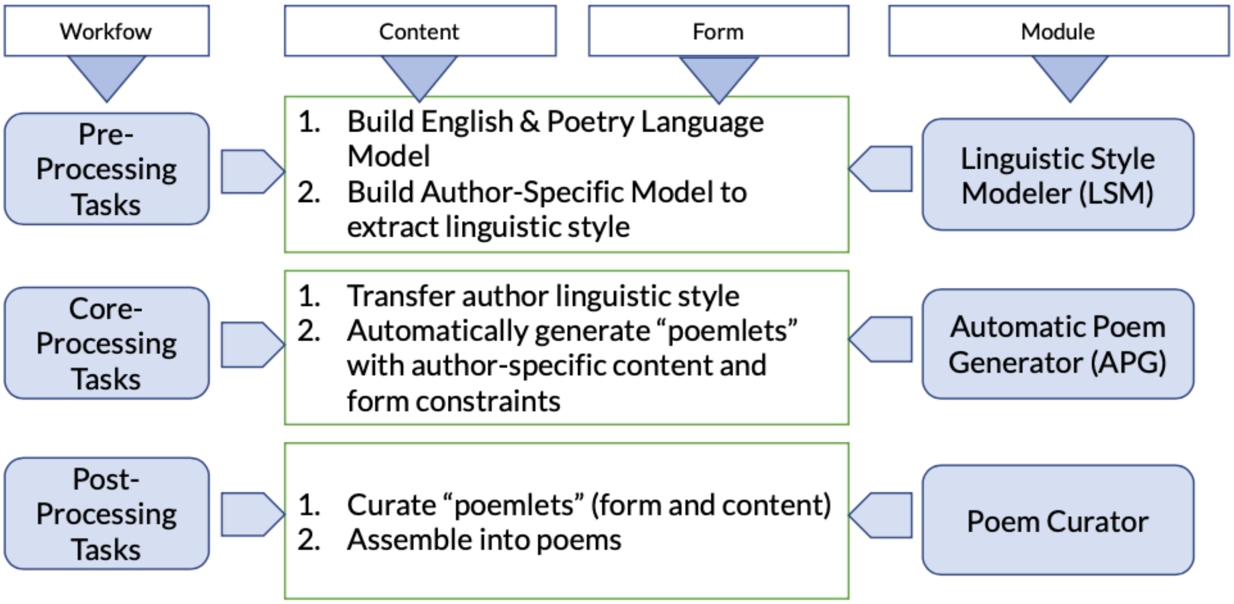

Figure 1: BACON approach (Pascual, A. R., 2021)

GAN ie. Generative Adversarial Network (Ian J. Goodfellow et. al., 2014) has been used extensively to generate art. It follows a creative process as described in figure 2. GAN's use adversarial process to generate output ie. It uses two architectures working against one another to generate new outputs. It works well to generate styles which it has seen but fails in subjective artistic changes for example, An art with deformations produced by GANs are surprising as they are not able to imitate human face properly and thus deformations do not look like a useful art.

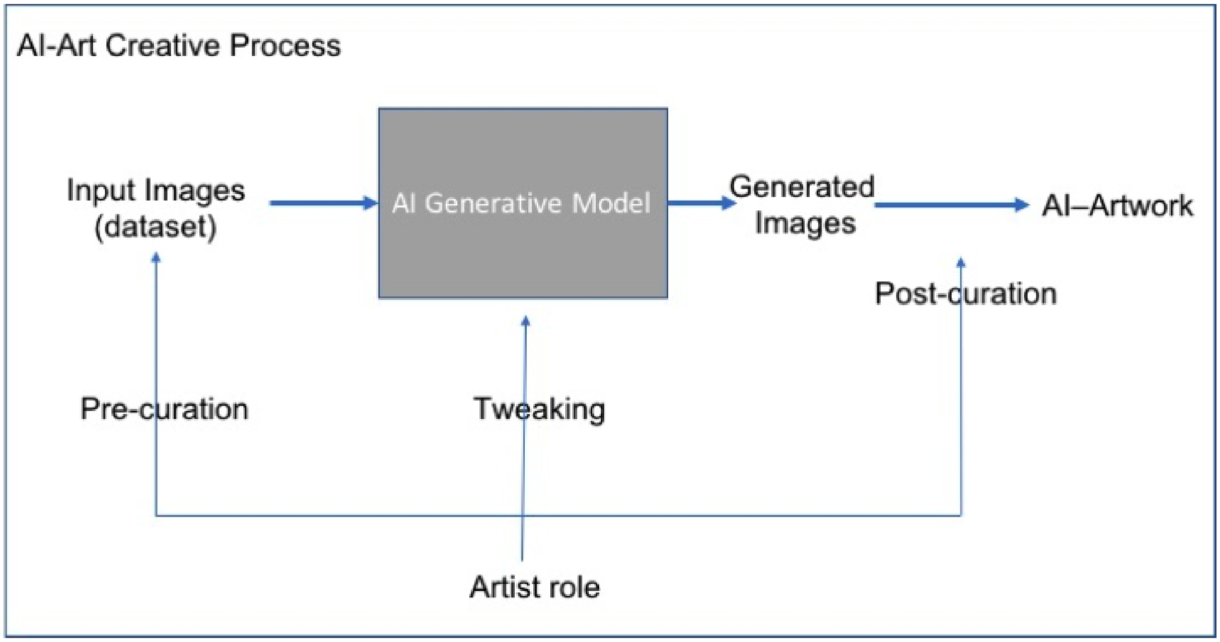

Figure 2: AI-Art Creative process

Creative Adversarial Networks ie. CAN (Elgammal, A. M., Liu, et. al. , 2017) was introduced to push the creativity in machines ie. to become more creative and not just generative. CAN (figure 3) is a variant of GAN which was based on a theory from psychology proposed by Colin Martindale (Martindale, 1990). It follows the process of how artists first learn various art forms and then start trying out newer forms by moving away from the learnt notion. CAN uses ambiguity in the style to achieve novelty. It is trained using two opposing principles: 1. It allows the model to follow the aesthetics of the art introduced to the model ie. to learn the art distribution 2. It penalizes the model if it emulates an art already seen by the model. This helps in creating art which is novel but not too far from the original style which leads to its usefulness. This process is really creative as it is able to generate novel art which is surprising yet useful from the perception of humans. On further investigation by the author, using a visual turing test, it showed that human subjects were not able to differentiate whether the art was made by a human artist or CAN. Human subjects described the CAN generated images as “intentional”, “inspiring” as well as “communicative”.

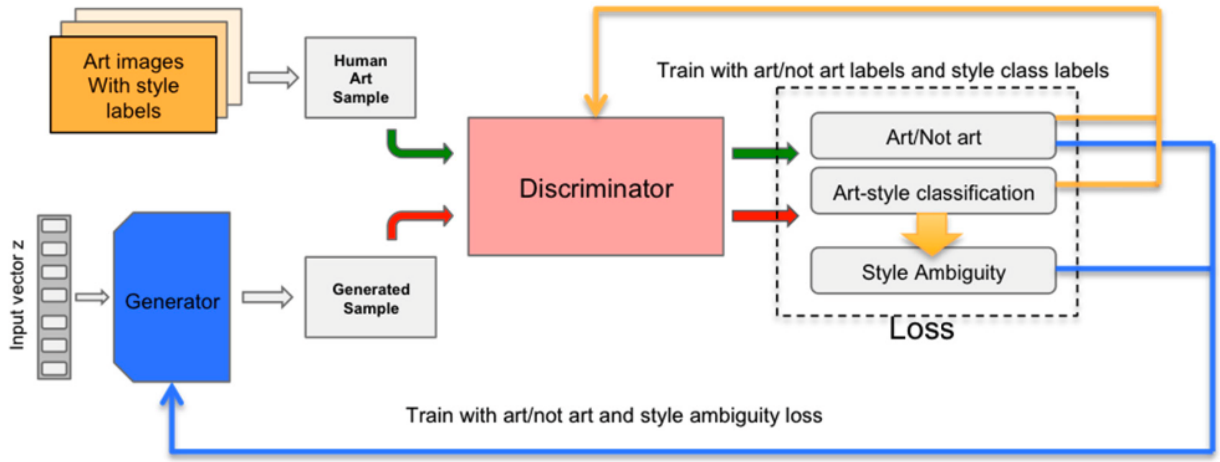

Figure 3: Creative Adversarial Network

Conclusion

Creativity is indeed an important aspect of human life occurring in every sphere. Progress in the modeling of creativity by AI models will help sustain the usefulness of AI in every sector especially in Art. It will in turn make the models more interpretable and generic than today which will be a big positive step toward Strong AI. Current AI methods lack the transformational creativity which is needed to create completely novel outputs along with its usefulness. It will require further research in the area of knowledge representation and reasoning to create better semantic representations which can be combined with deep learning to create useful and newer ideas. Subjectiveness is an important aspect of creativity which needs to be modeled in AI systems to make it more valuable. We need to use the grammar associated with every area to enhance the process of creative generation, for example, the use of music grammar as semantic representation during music generation. Evaluations for the generation process still at large remain human based. Automation in evaluation will further enhance the creative process that models take to learn and model new ideas. It will help in searching useful transformations and prune non valuable paths automatically. We are still at the beginning of AI creativity and research in future years in this direction will definitely create more creative systems to generate novel and valuable ideas as well as aid human creativity.

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